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Has the COVID-19 pandemic affected travellers' willingness to wait with real-time crowding information?

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ABSTRACT

Travel preferences in public transport (PT) have been substantially affected by the COVID-19 crisis, with rising emphasis on on-board safety and comfort aspects. Hence, real-time crowding information (RTCI) might have become even more instrumental in supporting travel decisions in congested urban PT systems. This study investigates the willingness to wait (WTW) to reduce (or avoid) overcrowding with RTCI in urban PT (bus and tram) journeys, analysing pre- vs. post-COVID travel behaviour attitudes. Stated-preference data and (subsequently estimated) choice models indicate that, while the pre-COVID WTW was primarily driven by mere possibility to avoid an overcrowded first departure, the post-COVID propensity to wait is strongly associated with expectations of seat availability in second departure as well. The ex-post WTW with RTCI seems to have become less-dependent on individual characteristics and more prominent for time-critical (obligatory) trips as well. Our findings underpin the rising relevance of passenger overcrowding in urban PT journeys. Moreover, they help better understand the potential of RTCI in post-pandemic recovery of PT ridership.

1. Introduction

Travel behaviour in public transport (PT) systems is shaped by multiple factors, including passenger overcrowding – a recurrent problem in high-density urban transportation networks. Rising (over) crowding reduces the relative attractiveness, comfort and safety perceptions of PT travel options. Moreover, it may lead to system failure in oversaturated PT networks – manifested in form of denied boardings, demand–supply feedback deteriorations etc. (Tirachini et al., 2013; Cats et al., 2016). Crowding impacts upon travel behaviour have been widely studied in state-of-the-art literature (e.g. (Wardman and Whelan, 2011; Tirachini et al., 2013; Hoercher et al., 2017; Yap et al., 2020) and references cited therein).

Meanwhile, the recent COVID-19 pandemic has profoundly affected urban PT systems worldwide, leading to plunging PT ridership and deteriorating service effectiveness (Basnak et al., 2022; Downey et al., 2022; Marra et al., 2022). Numerous studies worldwide have observed the negative correlation between human mobility and the COVID-19 spread (Lee and Eom, 2023). In response, policymakers introduced wide measures aimed at curbing the individual travel. The PT services were subject to reduced capacity restrictions, which in conjunction with infection risks have exacerbated the perceived risks of travelling in higher crowding conditions (Esmailpour et al., 2022; Shelat et al., 2022b). During the peak pandemic periods of 2020 – 2021, passenger volumes declined by even up to 50–80 % in urban areas worldwide (Xi et al., 2023). Though PT operations have been gradually restored to normal conditions as pandemic subsided, the COVID-19 restrictions have left yet lingering ramifications for passengers' travel behaviour (Tirachini and Cats, 2020; Gkiotsalitis and Cats, 2021). Emerging evidence points to shifts in travellers' decision-making patterns that may remain significant post-COVID – such as the popularity of work-from-home patterns (Sun et al., 2022; Xi et al., 2023) or aversion to PT overcrowding (Flugel and Hulleberg, 2022; Shelat et al., 2022b; Kapatsila et al., 2023). Decreasing PT ridership and rising private car dependency are especially valid risks of post-COVID travel pattern shifts (Lizana et al., 2024). The post-COVID PT systems face major challenges, which – if left unaddressed – may induce the risk of negative loop between declining passenger numbers, deteriorating profitability and service cuts, and worse overall travel conditions (incl. higher crowding) (Downey et al., 2022). Hence, the prospects of new ITS-based solutions

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should be explored to mitigate (over)crowding risks, reassure passengers, and ultimately – utilize the PT resources efficiently under real-time demand conditions (Lee and Eom, 2023).

1.1. Literature review

Passenger overcrowding influences travel decisions in PT networks in various ways, as observed in state-of-the-art (Tirachini et al., 2013; Gentile and Noekel, 2016). These involve shifts in: route choices, modal choices, departure time choices, trip frequencies, trip destinations, as well as trip chains' adjustments, monetary trade-offs (willingness to pay), and/or trip cancelling. Disutility of (over)crowding is quantified by means of crowding penalties, i.e. an equivalent rate of travel attribute – journey time, monetary fare, generalized travel cost – that passengers are willing to trade-off to travel in less-crowded conditions. A common measure is value-of-time (VoT) crowding penalty, which represents the journey time multiplier of a travel option with specific on-board crowding conditions. The VoT crowding valuations are typically obtained in stated-preference (SP) experiments (Whelan and Crockett, 2009; Batarce et al., 2015; Bansal et al., 2022; Basnak et al., 2022; Fedujwar and Agarwal, 2024), where multiple (hypothetical) choice scenarios can be analysed. A certain caveat is that SP valuations are prone to overestimation bias of crowding disutility. The second approach involves revealed-preference (RP) studies, where crowding valuations are deduced from real-world travel records (Hoercher et al., 2017; Tirachini et al., 2016; Yap et al., 2020; Yap et al., 2023). Though more accurate, the RP approach is not always feasible as obtaining reliable, (noise-free) data is often challenging.

A less-explored aspect of VoT crowding valuations involves their trade-offs against waiting time. This phenomenon of **willingness to wait (WTW)** to avoid (or reduce) the negative effects of overcrowding may be observable especially in high-frequency urban PT networks, where passengers may deliberately skip an overcrowded departure and accept additional waiting time to board a later, less-crowded departure (Drabicki et al., 2023; Lee et al., 2024). This notion has been hitherto explored in a few studies, predominantly within the SP setting. The SP findings show that share of PT users willing to wait additional few minutes may vary between 10 % (to avoid minor crowding) to even 75 % (to avoid severe overcrowding) (Kroes et al., 2014). Factors influencing (higher) WTW probability include: non-commuting trip purposes, arrival time flexibility, higher (users') age, emphasis on travel time productivity (Kattan and Bai, 2018; Kim et al., 2009; Preston et al., 2017; Shelat et al., 2022b; Lee et al., 2024). Waiting time acceptance in order to mitigate on-board crowding in short-range, urban PT trips may reach up to 10 – 15 [mins] and rises evidently above a given (perceived) threshold of overcrowding (Drabicki et al., 2023). The WTW behaviour is also found to be relevant in context of regional rail trips, where acceptable waiting times range between 8 and 23 [mins], and VoT crowding multipliers for a 30-minute trip are approx. 1.3 – 1.7 (Preston et al., 2017). Pre-trip planning process can involve even higher WTW of up to 20 – 30 [mins] for a less-crowded train (Burger et al., 2023).

Arguably, passengers' WTW behaviour can be incited by providing real-time information on passenger loads on-board the next PT vehicle departures. This is nowadays feasible within modern ITS framework by means of generating and disseminating the **real-time crowding information (RTCI).** Practical implementation of the RTCI systems is gaining momentum especially in the aftermath of COVID-19 pandemic crisis, as witnessed by latest developments in the US cities, e.g. Boston (MBTA), San Jose (VTA), Washington D.C. (WMATA), as well as in other locations worldwide (e.g. London, Stockholm, Sydney, Tokyo, Dutch Railways, Moovit). These have been accompanied by research interest devoted mostly to developing models for simulating the impacts of RTCI deployments (Drabicki et al., 2021, 2022; Nuzzolo et al., 2016; Peftitsi et al., 2022) and crowding prediction algorithms (Jenelius, 2020; Więcek et al., 2019). However, the impact of RTCI upon WTW has only been explored in a couple of studies (cited above), with findings mostly based on pre-COVID observations.

Crucially, passengers' perceptions of PT overcrowding have been substantially affected by COVID-19 pandemic and the associated distancing measures. Table (Table 1) summarises the most relevant literature findings. Overall, results obtained during or right after the COVID pandemic indicate that passengers attach greater value to aspects related to the mitigation of overcrowding (Downey et al., 2022; Karatsoli et al., 2024), availability of seats (Aghabayk et al., 2021), perceived travel safety (Esmailpour et al., 2022), face mask use and vehicle sanitisation (Awad-Nunez et al., 2021; Basnak et al., 2022; Shelat et al., 2022a). Travelling inside closed-space buses, trams or trains seemingly invokes greater concerns of contagion spread, especially if safe distance cannot be guaranteed due to on-board crowding (Tirachini and Cats, 2020; Devasurendra et al., 2022; Karatsoli et al., 2024; Cho et al., 2024). A couple of studies have noted lower attractiveness of rail trips vs. bus journeys (Cho and Park, 2021; Yap et al., 2023), which is attributable e.g. to differences in perceived air ventilation on-board (Helfers et al., 2024). Certain user groups have become particularly apprehensive of travelling in overcrowded conditions, due to perceived infection risks, including older-age, lower-income or female travellers (Bansal et al., 2022; Basnak et al., 2022; Shelat et al., 2022b; Cho et al., 2024). PT (over)crowding can induce higher propensity to use private cars, as well as raise the relative utility of walking and cycling modes (Iglesias and Raveau, 2024). Evidence shows that COVID-induced concerns of PT crowding may have already decreased since peak pandemic periods in 2020, albeit by limited amount (Iglesias and Raveau, 2024; Kapatsila et al., 2023), and it remains unclear whether they will fully subside over time (Flugel and Hulleberg, 2022; Rossetti and Daziano, 2024). Further monitoring is still needed to evaluate the eventual, long-term stability of users' perceptions. Nevertheless, though exact VoT estimates differ in individual sources, the perceived PT crowding disutility is observed to be up to 10 – 40 % greater when compared to the pre-pandemic levels (Basnak et al., 2022; Aghabayk et al., 2021; Cho and Park, 2021).

2. Research gap and objectives

A rapidly growing stream of literature works explores travel behaviour shifts due to the COVID-19 crisis. Despite that, an empirical underpinning of post-COVID RTCI influence on travel decisions is still lacking. This is especially valid in the context of new travel behaviour phenomena – such as WTW – that can be stimulated by RTCI provision. Lack of such ex-post vs. ex-ante analysis hampers the development of solutions which could effectively address the post-pandemic challenges of PT systems.

We conduct a comparative analysis of pre- vs. post-COVID changes in passengers' WTW with RTCI. Our research questions are summarized as follows:

1. What is the stated WTW to avoid (or reduce) overcrowding in urban PT in the aftermath of COVID-19 pandemic crisis?
2. What shifts in the WTW with RTCI are traceable before vs. after COVID-19 crisis, and what choice factors play a more (or less) important role?
3. What are the implications for RTCI solutions in urban PT systems?

A key contribution of this study is an evidence-based investigation of WTW with RTCI under pre- vs. post-COVID conditions. Our focus is on passengers' crowding valuations in the urban PT context, i.e. bus and tram trips. In general, our findings highlight that the WTW with RTCI is likely to have become a prominent travel behaviour phenomenon, and passengers' perceptions of RTCI utility have become more nuanced post-COVID. In specific cases, however, the utility of RTCI might have decreased compared to pre-COVID levels, highlighting passengers' concerns of on-board overcrowding (and e.g. associated infection risk). Outputs are estimated in the form of mixed logit choice models,

Table 1
Up-to-date literature findings' summary of COVID-19 impacts upon crowding valuations in public transport.

Study (source)	Scope and methodology	Main findings
Aghabayk et al (2021)	• SP survey in Tehran metro (Iran) • 2 data collection stages: **pre-COVID** (autumn 2019) and **during COVID** (autumn 2020) • crowding and travel time valuations acc. to methodology of Tirachini et al (2017) • mixed logit modelling	• VoT crowding multipliers during COVID higher on average by 15 % (sitting) to 27 % (standing conditions) • changes vs. pre-COVID: higher value of having a seat on the train; lower travel comfort especially at medium crowding levels (1 pass./m2)
Bansal et al (2022)	• SP survey in London Underground (UK) • data collection **during COVID** (spring 2021) • crowding and travel time valuations, plus 'COVID-specific' attributes (daily infection rate, vaccine adoption, face-mask policy) • latent class logit modelling	• VoT sitting crowding multiplier peaking at 1.73, i.e. 6 % higher compared to pre-COVID *meta*-analysis of Whelan, Crockett (2009) • low sensitivity to crowding among: low-income travellers; men and users under 40 y/old • crowding penalty at max. (technical) capacity up to 2 times greater with information on COVID infection spread (prevalence rate)
Basnak et al (2022)	• SP survey in Santiago metro & buses (Chile) • data collection **during COVID** (Aug – Oct 2020) • crowding and travel time valuations, plus trip cost & 'COVID-specific' attributes (face mask use, disinfection frequency) • latent class and mixed logit modelling	• VoT crowding multipliers higher by up to 10 %, compared to pre-COVID results of Batarce et al (2016), Tirachini et al (2017) • max. VoT crowding multiplier: 2.55 at the 4 [standees per sq. m] • extra crowding penalty with decreasing share of face-mask users (max. 1.5–2.0 times greater) • higher sensitivity to crowding among: high-income and frequent travellers; women and users over 30 y/old • no significant differences between sitting or standing in crowded conditions
Cho et al (2024)	• SP survey in Seoul (South Korea) • data collection **during COVID** (Nov 2020) • crowding and travel time valuations, incorporating latent behaviour characteristics • exploratory factor analysis plus multinomial logit modelling	• 4 attitudinal user groups with different crowding valuations: (a.) fear of disease, (b.) PT preference, (c.) time-sensitivity, (d.) car preference • max. VoT crowding multipliers: overall ca. 1.4 (bus) to 1.6 – 1.8 (subway) at 200 % load factor, increasing to 1.8 and 1.7 – 2.0 for COVID-sensitive travellers • COVID-sensitive bus users: sitting crowding penalty – similar or even higher than standing penalty (perceived closeness) • subway users: standing crowding penalty – higher impedance (vs. sitting)
Cho and Park (2021)	• SP survey in Seoul metro & buses (South Korea) • 2 data collection stages: **pre-COVID** (Oct 2018) and **during COVID** (Nov 2020) • crowding and travel time valuations measured • random parameter mixed logit modelling	• VoT crowding multipliers during COVID higher by 4 % (buses) to 23 % (metro) • changes vs. pre-COVID: little influence of users' exposure frequency to PT crowding upon VoT crowding multipliers
Fluegel, Hulleberg (2022)	• SP survey in Oslo and Trondheim (Norway) • 3 data collection stages: **pre-COVID** (Nov 2018); **during COVID** (Apr 2021 and Nov 2022); and **post-COVID** (May 2022) • crowding and travel time valuations measured • mixed logit modelling	• post-COVID crowding penalties higher than pre-COVID rates, and somewhat lower than during COVID • max. VoT crowding multipliers post-COVID higher by ca. 40 – 60 % (vs. pre-COVID) and lower by ca. 20 – 40 % (vs. during COVID) • crowding multiplier while sitting witnessed relatively higher post-COVID increase
Iglesias, Raveau (2024)	• RP survey in Santiago (Chile) • data collection **during COVID** (Nov 2020 and May 2021) • crowding and travel time valuations, including modal shifts from/to active modes • MIMIC (Multiple Indicator Multiple Causes) framework plus hybrid discrete choice modelling	• certain (limited) decline in crowding aversion from Nov 2020 to May 2021 • walking preferred over PT for travel times under 4 [mins] (little/no crowding) to 9–12 [mins] (high crowding) • higher inclination to use walking/cycling than pre-COVID for shorter trips, regardless of PT crowding
Kapatsila et al (2023)	• SP survey in Metro Vancouver (Canada) • data collection **during COVID** (Dec 2020 and May 2021) • crowding and travel time valuations, incorporating attitudinal characteristics • hybrid discrete choice and latent class modelling	• certain (limited) decline in crowding aversion from Dec 2020 to May 2021 • PT demand elasticity of crowding 1.5 – 2.0 times higher than pre-COVID • morning peak commuters: (relatively) lowest concerns of crowding and safety (exposure effect) • up to 30 % of passengers potentially responsive to PT crowding information
Rossetti, Daziano (2024)	• SP survey in the New York City subway (USA), plus ride-hailing and microtransit • data collection **during COVID** and **post-COVID** (Jan – Mar 2022) • crowding and travel time valuations, plus 'COVID-specific' attributes (face mask use, vaccination rate) • mixed logit modelling	• post-COVID crowding multipliers on subway (max. VoT multiplier of 1.25) lower than during COVID (1.4 – 1.5) • face mask use rate no longer relevant in post-COVID crowding valuations
Shelat et al (2022a)	• SP survey in the NS trains (the Netherlands) • data collection **during COVID** (Dec 2020) • crowding and travel time valuations, incl. 'COVID-specific' risk perception trade-offs • linear regression with hierarchical information integration framework plus mixed logit modelling	• crowding penalties during COVID: willingness to pay ca. 4 times greater in case of longer trips (30 + [mins]) to get a seat, mandate mask use or increase sanitisation on-board • risk perception impacts: crowding and infection rate (increasing), mask mandates and sanitisation (decreasing)
Shelat et al (2022b)	• SP survey in the NS trains (the Netherlands) • data collection **during COVID** (May 2020) • crowding and <u>waiting</u> time valuations, plus 'COVID-specific' attributes (exposure duration, infection rate) • latent class logit modelling	• 2 latent user segments: (a.) 'infection indifferent' and (b.) 'COVID-conscious', with significantly different VoT values • VoT crowding factors during COVID expressed as an acceptable waiting time to reduce 1 person on-board: 1.0 [mins] in class (a.) and 8.8 [mins] in class (b.) • WTW to reduce overcrowding up to 17 and 74 [mins] for classes (a) and (b.) • exposure duration (in-vehicle time) found to be an insignificant choice factor • class (a.) likely to be female and elderly users, class (b.) frequent PT travellers
Yap et al (2023)	• RP investigation in London metro & buses (UK), based on APC data (load weights) • 2 data collection stages: **pre-COVID** (Feb 2020) and **post-COVID** (Jun 2022) • crowding and travel time valuations (route choice trade-offs) • max. likelihood estimation with path size logit modelling	• post-COVID crowding penalty rising by 0.42 per each increase in average standing density – compared to an 0.22 average in pre-COVID literature • max. VoT crowding multiplier: 2.68 at the 4 [standees/sq m.] • lower attractiveness of metro vs. bus in-vehicle time (15 % change post-COVID) • no changes in walking or waiting time valuations with respect to in-vehicle time • crowding level upon boarding provides the best explanatory power

accounting for panel and heterogeneity aspects. As such, they allow for numerical assessment of WTW probability as a function of RTCI content and trip- and population-related characteristics.

Implications of this research reinforce the future value and potential of RTCI, which may play an even more important role in the post-pandemic PT service recovery. Propensity to avoid overcrowding seems to be even higher post-pandemic, also for short-range urban PT trips. Hence, crowding and comfort aspects will likely retain importance as choice factors in urban PT travel in the near future. Related scientific and practical conclusions are discussed at the end of this study.

3. Methodology

3.1. Survey design and data collection

To analyse the WTW with RTCI, we conducted stated-preference (SP) surveys and used their outcomes to develop discrete choice models. Our research investigation was performed in 2 data collection stages:

- 'pre-COVID' investigation – March 2019 ($n = 377$ respondents),
- 'post-COVID' investigation – May 2022 ($n = 424$ respondents).

Both research stages utilise the methodology akin to that given in (Drabicki et al., 2023), summarised below. The SP survey questionnaire contained 14 questions in total. It consisted of the four following parts:

1. Introduction and own (general) experience of PT overcrowding.
2. Current PT trip context – trip purpose, time-criticality (i.e. propensity to arrive on-time), frequency of travelling along this O-D route, journey time, service frequency.
3. Stated-choice (SC) experiment – WTW with hypothetical RTCI on next 2 departures for the current trip (explained below).
4. Socio-demographic data.

The central part of survey was a panel set of SC experiments (Fig. 1), resulting from multiple focus-group discussions and relevant in the decision-making context of the WTW phenomenon. Respondents were presented with a hypothetical RTCI on crowding levels of the 2 next bus/tram departures of their current travel route. They were asked to indicate their preferred choice between taking the first departure – departing now, but with higher on-board (over)crowding, or taking the second departure – less-crowded, yet departing 5 or 10 min later. Both choice options had the same remaining trip characteristics, i.e. journey time, propensity to arrive on-time etc., as specified by respondents themselves in earlier part of the SP survey. Thus, our SC experiment represented a binary choice context, where respondents exercised trade-offs between: (1.) possibility to reduce on-board overcrowding, indicated by the RTCI, vs. (2.) required extra waiting time. The following in-vehicle crowding scenarios were included in survey design:

- case (A): 1st departure – moderate standing crowding (RTCI level 3), 2nd departure – seats available (RTCI level 2),
- case (B): 1st departure – high overcrowding (RTCI level 4), 2nd departure – moderate standing crowding (RTCI level 3),
- case (C): 1st departure – high overcrowding (RTCI level 4), 2nd departure – seats available (RTCI level 2).

Combinations of 3 possible RTCI scenarios and 2 waiting time values (5 or 10 min) yielded in total 6 SC scenarios, presented to each respondent.

Surveys were conducted among passengers at urban PT stops in Krakow (i.e., second-largest city in Poland of approx. 1.2 m metro-area population). Pilot surveys were conducted first to improve the questionnaire, and to ensure that respondents can answer its contents meaningfully within max. 3 – 5 min (the ultimate completion rate was ca. 90 %). A randomized sampling strategy aimed to reflect the typical demand pattern of urban PT users in Krakow as closely as possible (Table 2). Timing of both (pre- and post-COVID) survey rounds ensured that the case-study urban PT system was free of any disruptions or social distancing restrictions, which could have impaired the reliability and plausibility of collected responses.

3.2. Willingness-to-wait model estimation

Next, the SP data served as the basis for discrete choice modelling of the WTW with RTCI. Our setup reflects a binary choice context, in accordance with the random utility maximization (RUM) theory (Ben-Akiva and Lerman, 1985) and analogous to modelling approach of (Drabicki et al., 2023). The RUM paradigm is well-suited to describe the decision-making context where users choose an alternative that maximises their perceived utility. Choice probability is evaluated between the utility U_1 of boarding now the first departure vs. utility U_2 associated with waiting and boarding (later) the second departure. Assuming that the utility U_1 is fixed constant ($U_1 = 0$), the $U_2 = U_{WTW}$ essentially expresses the willingness to wait (WTW) utility, i.e. the relative (dis)utility associated with deliberately waiting for a second, less-crowded PT departure (Eq. (1)):

$$P(U_2) = \frac{exp(U_2)}{exp(U_1) + exp(U_2)} = \frac{exp(U_{WTW})}{1 + exp(U_{WTW})} \tag{1}$$

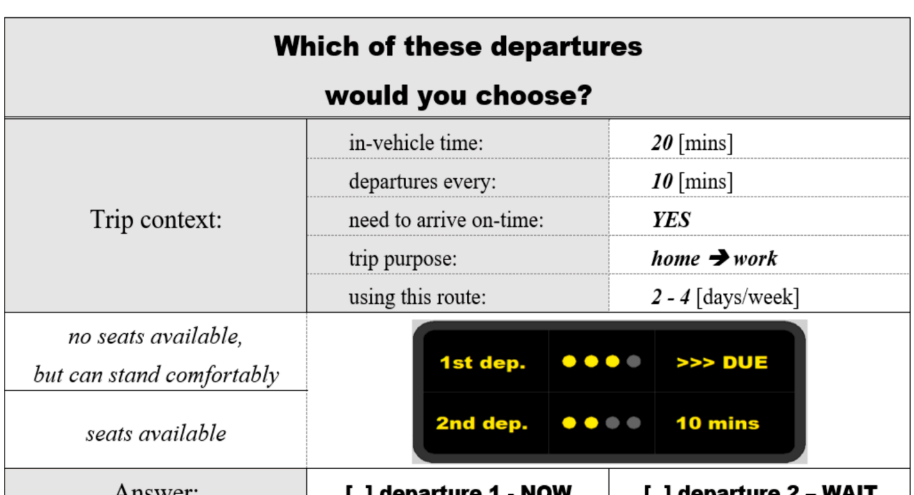

Fig. 1. Example of the SP choice experiment question.

The U_{WTW} utility consists of the systematic utility V_{WTW}, plus a random error term ε_{WTW} (normally distributed, with mean zero value). The systematic WTW utility is, in turn, a function of a vector of taste (preference) co-efficients $\boldsymbol{\beta_k}$ and corresponding attribute values $\boldsymbol{X_k}$ (Eq. (2):

$$V_{WTW} = \sum_{k=1}^{K} \boldsymbol{\beta_k} {}^* \boldsymbol{X_k} \tag{2}$$

The attribute set K contains trip- and population-related characteristics valid for a given choice situation. Explanatory variables of the vector $\boldsymbol{X}$ are included either as dummy variables δ_k (equal to 1 if the parameter k is valid in a given choice situation, and 0 otherwise); or as (continuous) time variables t_k – in case of waiting time and in-vehicle journey time.

We estimate two WTW model specifications, both in form of mixed logit (MXL) formulation. The base MXL model consists of 2 key attributes of the our SC experiment (Eq. (3): (1.) RTCI utility $\beta^{s}_{RTCI} \cdot \delta^{s}_{RTCI}$ and (2.) waiting time (dis)utility $\beta_{wt} \cdot t_{wt}$.

$$V_{WTW} = \beta^{3-2}_{RTCI} {}^* \delta^{3-2}_{RTCI} + \beta^{4-3}_{RTCI} {}^* \delta^{4-3}_{RTCI} + \beta^{4-2}_{RTCI} {}^* \delta^{4-2}_{RTCI} + \beta_{wt}(\mu, \sigma) {}^* t_{wt} \tag{3}$$

The base MXL model reflects the direct trade-off between the advantage of reduced (over)crowding between first and second PT departure, as informed by the RTCI system, versus the disadvantage of extra waiting time (for second departure). Utility of RTCI is represented by case-specific dummy variables $\beta^{s}_{RTCI} \cdot \delta^{s}_{RTCI}$, denoting the RTCI levels of first and second departure in the choice scenario s – in accordance with the SC experiment setup (outlined above):

- $\beta^{3\text{-}2}_{RTCI}$ – RTCI utility in case (A): 1st departure – RTCI level 3 vs. 2nd departure – RTCI level 2,
- $\beta^{4\text{-}3}_{RTCI}$ – RTCI utility in case (B): 1st departure – RTCI level 4 vs. 2nd departure – RTCI level 3,
- $\beta^{4\text{-}2}_{RTCI}$ – RTCI utility in case (C): 1st departure – RTCI level 4 vs. 2nd departure – RTCI level 2.

The MXL approach allows to capture the unobserved heterogeneity in our panel survey data. This is modelled by means of mixing distribution applied to the waiting time co-efficient, assumed to be a normally distributed value $\beta_{wt}(\mu,\sigma)$.

The second WTW model specification is the extended MXL model (Eq. (4). It is the extension of base MXL model with a set of trip- and individual-related attributes, which were found to be statistically relevant in at least one of the SP investigation stages (pre- or post-COVID). These attributes are included by means of dummy variables (analogous to RTCI utility) and express the influence upon WTW (dis)utility of the following aspects:

- trip frequency ($\delta_{commute} = 1$ if respondent performs this trip at least twice a week),
- age ($\delta_{age50\text{-}65} = 1$ if respondent is 50 – 65 years old; $\delta_{age65plus} = 1$ if more than 65 y/old),
- trip time-criticality (δ_{RTCI}=1 if respondent has to arrive by certain time at the destination),
- gender ($\delta_{female} = 1$ if respondent is female),
- in-vehicle journey time (total remaining time to trip destination – t_{ivt} in [mins]),
- own PT travel experience ($\delta_{past\_overcr} = 1$ if respondent frequently experience overcrowding in their PT trips; $\delta_{past\_seats} = 1$ if respondent frequently encounters available seats in their PT trips).

$$V(WTW) = \beta^{3-2}_{RTCI} {}^* \delta^{3-2}_{RTCI} + \beta^{4-3}_{RTCI} {}^* \delta^{4-3}_{RTCI} + \beta^{4-2}_{RTCI} {}^* \delta^{4-2}_{RTCI} \tag{4}$$

Next, based on discrete choice modelling results, we compute the distribution of waiting time thresholds for each RTCI scenario s. The ratio between marginal utilities of RTCI β^{s}_{RTCI} and waiting time β_{wt} yields WTW time thresholds t^{WTW}_{s} in [mins]. This value can be interpreted as max. acceptable trade-off between extra waiting time required to travel on-board a less-crowded second PT departure from the same stop. Since waiting time is a distributed variable, we perform Monte Carlo simulations with 100,000 draws of wait time co-efficients (Sillano and Ortuzar, 2005), and after discarding unrealistic values (ca. 1.5 % of total sample) we compute output WTW distributions. The estimated WTW thresholds can be then further used to estimate WTW crowding multipliers (Preston et al., 2017; Drabicki et al., 2023), applicable in PT simulation models and cost-benefit analyses.

4. Results

4.1. Descriptive statistics

Starting from descriptive statistics, a broad overview of SP survey results reveals the significance of the WTW with RTCI, as well as exposes major differences between both pre- and post-COVID samples (Fig. 2). The 2019 pre-COVID results indicate a substantial propensity to avoid high overcrowding (RTCI level 4) in the first vehicle, regardless of crowding reduction inside the second departure. Ca. 75 % of respondents would choose the less-crowded PT vehicle arriving in 5 [mins], and for a 10-minute wait the corresponding rate oscillates around 45 %. Meanwhile, the 2022 post-COVID findings point towards high importance of crowding levels on-board not merely the first, but also the second PT departure. Information on possibility to avoid high overcrowding (RTCI lvl 4) in exchange for a much less-crowded departure with seats available (RTCI lvl 2) incites a substantially greater WTW response rate than pre-COVID, reaching over 90 % for a 5-minute and ca. 55 % for a 10-minute wait. Contrarily, however, if on-board conditions of the second departure imply moderate ‘standing’ crowding (i.e. shifting from RTCI lvl 4 to lvl 3), the WTW probability drops down to ca. 60 % and 20 %, respectively. In the third possible scenario, respondents’ willingness to avoid a moderately crowded vehicle (RTCI lvl 3) in order to board a later one with seats available (RTCI lvl 2) remains analogous across both pre- and post-COVID samples. Approx. 30 % of them would accept a waiting time of 5 [mins], and ca. 10 % would wait for 10 [mins].

Detailed WTW results, depending on selected trip and population characteristics, are presented in (Table 3). Comparison of pre- vs. post-COVID findings shows that certain choice attributes have a noticeably different impact upon respondents’ choices. In a broad overview though, post-COVID responses exhibit relatively lower influence of trip- and demographic-related factors upon WTW with RTCI. This is especially observable in case (C), i.e. an abrupt reduction in overcrowding (RTCI lvl 4 to 2), where waiting for a less-crowded departure is the most

Table 2
Size and demographic composition of the SP survey data, compared with the general PT user population data in Krakow, acc. to the comprehensive travel survey results (Szarata, 2015).

	Survey sample (absolute, *% share*)				**Krakow travel survey sample (2014)** *(%)*
	Pre-COVID (2019)		**Post-COVID (2022)**		
Total respondents	377	*100.0 %*	432	*100.0 %*	*100.0 %*
Gender:					
Women	198	*52.5 %*	230	*53.2 %*	*57.6 %*
Men	179	*47.5 %*	202	*46.8 %*	*42.6 %*
Age:					
18 – 25	164	*43.5 %*	134	*31.0 %*	*26.6 %*
26 – 40	118	*31.3 %*	99	*22.9 %*	*28.7 %*
41 – 50	41	*10.9 %*	59	*13.7 %*	*11.7 %*
51 – 65	18	*4.8 %*	90	*20.8 %*	*14.9 %*
> 65	36	*9.5 %*	50	*11.5 %*	*18.1 %*

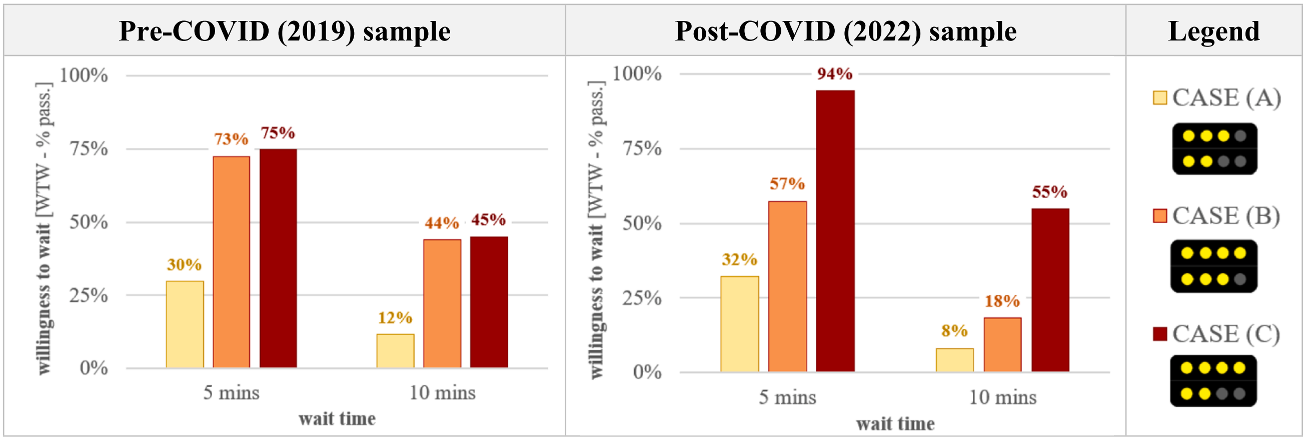

Fig. 2. Survey results – overall WTW with RTCI in the pre- (left) vs. post-COVID (right) sample.

favourable option in context of most choice attributes.

With regards to specific attributes, influence of trip time-criticality remains relevant, but its influence is lower post-COVID. Similar patterns can be traced in terms of trip purposes, though obligatory trips (e.g. commuting) retain generally lower WTW probabilities. Propensity to wait has become greater in case of non-home-based trips and more aligned with leisure purposes. Otherwise, respondent's age remains relevant, as the WTW increases substantially for those aged 50–65 years, and even further for the 65 + year-olds. The post-COVID research suggests somewhat higher WTW for those aged 40 – 50 years as well. It also highlights rising importance of respondent's gender, as females are now more inclined to wait to avoid on-board overcrowding. Otherwise, the WTW with RTCI seems not to be significantly influenced by the remaining journey time (to trip destination), nor trip frequency.

Next, we investigate the relation between WTW choices and respondents' own experience of (i.e., exposure to) different travel comfort in everyday PT trips (Fig. 3). Travellers who frequently encounter on-board overcrowding are less willing to wait for the second departure, with ca. 50–65 % opting for the first available trip in our SC experiment (depending on the RTCI scenario). Conversely, those who experience more often a seated PT journey express a greater WTW probability: ca. 40 % to even 80 % of those travellers would wait up to 10 [mins]. These tendencies are consistent across the pre- and post-COVID samples, with WTW choices rising post-COVID among respondents used to (frequent) availability of seats in PT journeys.

4.2. Model estimation results

Survey outputs are provided as an input to discrete choice model estimations. This is carried out by means of BIOGEME software (Bierlaire, 2023) and additionally verified with a tailored script developed in the Python 3.7 software. Estimation results for the base mixed logit (MXL) WTW model are presented in (Table 4). All the co-efficients are statistically significant at $p < 0.05$, and panel effects are accounted for in mixing distribution applied to waiting time (dis)utility β_{wt}. The larger (and more positive) value of the RTCI utility β^{s}_{RTCI}, the greater the resultant WTW probability. Conversely, the negative value of waiting time co-efficient β_{wt} represents rising (incremental) disutility of each additional minute of required waiting time (and thus lower WTW).

The pre-COVID estimates of base WTW model indicate that RTCI utility is roughly 3 times higher in both cases (B) and (C), i.e., with first departure being overcrowded (RTCI level 4), than in case (A) when its on-board conditions reduce to moderate standing crowding (RTCI level 3). However, the post-COVID picture is more nuanced: compared to case (A), the RTCI utility β^{s}_{RTCI} in the case (B) increases approx. by a factor of 1.7, yet in the case (C) it is again ca. 3 times higher. In general overview, the post-COVID utility of RTCI is relatively greater in case of information on seats available in the second departure (RTCI lvl 2).

In (Table 5) we present further estimation results for the extended WTW model formulation, before (left) and after (right) the COVID-19 crisis. These include additional individual- and trip-specific attributes, which were found to be statistically relevant. Respondent's age has a noticeable and positive correlation with the WTW utility, rising for those aged between 50 and 65 y/old and even further for elderly users. The $\beta_{age50\text{-}65}$ and $\beta_{age65plus}$ values are lower in the post-COVID estimates, implying that their influence upon WTW with RTCI has declined in the aftermath of pandemic crisis (i.e., post-COVID WTW probabilities differ less between distinct age categories). A similar but (opposite) negative correlation is observable in case of trip time-criticality ($\beta_{timecrit}$). The necessity to arrive on-time reduces the WTW utility in general, but the corresponding co-efficient value is ca. 3 times smaller in post-COVID estimations. Meanwhile, female gender (β_{female}) increases the WTW probability, and in contrast to previous factors – its relevance has increased compared to pre-COVID findings. Amongst the remaining MXL model attributes, commuter trips ($\beta_{commuter}$) – i.e. made at least 2 days per week – exhibit a (limited) negative influence upon the stated WTW, but the effect is not sufficiently significant at $p < 0.05$ in both investigation samples. Likewise, in-vehicle journey time (β_{ivt}) already had very minor influence upon pre-COVID WTW, and its impact has become negligible in post-COVID models. Its marginal disutility values are at least order of magnitude lower than those of waiting time disutility (β_{wt}). This correlates with state-of-the-art findings (Preston et al., 2017; Cho and Park, 2021; Shelat et al., 2022b). Additionally, the WTW is negatively correlated with respondents' frequent exposure to PT overcrowding (β_{past_overcr}), and conversely – positively correlated with own experience of seats' availability (β_{past_seats}). The latter aspect relatively grows in relevance in the post-COVID model. However, both factors are not statistically significant at the 95 % level.

Discrete choice modelling results can be further used to evaluate the ratio of marginal utilities of RTCI and waiting time. This yields average acceptable waiting times for a second, less-crowded PT departure t^{WTW}_{s} in [mins] in the given RTCI scenario s, plotted in (Fig. 4) and (Table 6). The pre-COVID plots reaffirm relatively greater relevance of trip time-criticality. Average acceptable WTW thresholds in pre-COVID investigation range between 3 and 8 [mins] for case (A) ($t^{WTW}_{3\text{-}2}$), and 4 – 13 [mins] for the cases (B) and (C) ($t^{WTW}_{4\text{-}3}$, $t^{WTW}_{4\text{-}2}$). In post-COVID estimates, case (A) exhibits similar mean values, but with wider dispersion of $t^{WTW}_{3\text{-}2}$ occurrences especially for time-critical trips. Conspicuous differences (vs. pre-COVID results) are particularly exposed in 2 instances: firstly, in the non-time-critical $t^{WTW}_{4\text{-}3}$ estimates – average of ca. 7 [mins] and diminishing probabilities for waiting times of 15 + [mins]; and secondly, in case of time-critical $t^{WTW}_{4\text{-}2}$ estimates – mean equal to ca. 11 [mins] and dispersion reaching up to 20 [mins]. Overall, the post-COVID acceptable WTW thresholds are more dissipated across wider waiting

Table 3
Survey results – WTW share vs. choice factors, pre- (left) and post-COVID (right).

	Pre-COVID (2019) sample *(n = 377)*						**Post-COVID (2022) sample** *(n = 432)*					
RTCI scenario:	case (A)			case (C)			case (A)			case (C)		
Max. acceptable wait time:	0	5 mins	10 mins	0	5 mins	10 mins	0	5 mins	10 mins	0	5 mins	10 mins
[mins]	WTW vs. **in-vehicle time**											
< 10	78%	16%	7%	47%	16%	37%	83%	17%	0%	0%	33%	67%
10 – 20	72%	18%	10%	22%	38%	41%	69%	25%	7%	7%	41%	52%
20 – 30	68%	20%	13%	21%	26%	53%	72%	20%	7%	5%	48%	47%
> 30	61%	18%	22%	28%	27%	45%	66%	25%	9%	5%	31%	63%
Need to arrive on-time?	WTW vs. trip **time-criticality**											
yes	84%	12%	4%	43%	33%	24%	79%	17%	5%	7%	50%	44%
no	60%	22%	18%	15%	25%	60%	60%	30%	10%	5%	32%	64%
origin dest.	WTW vs. **trip purpose**											
home – work	79%	15%	6%	46%	27%	26%	74%	22%	5%	6%	58%	36%
home – edu.	90%	10%	0%	35%	32%	32%	86%	11%	3%	8%	63%	29%
home – leisure	52%	19%	29%	10%	5%	86%	49%	41%	11%	4%	22%	75%
work – home	74%	14%	12%	15%	38%	47%	72%	28%	0%	2%	27%	71%
edu. – home	64%	31%	5%	22%	26%	52%	88%	12%	0%	12%	49%	39%
leisure – home	31%	17%	51%	6%	17%	77%	53%	27%	20%	2%	11%	87%
non-home-based	80%	14%	6%	32%	36%	32%	52%	35%	13%	6%	45%	49%
gender	WTW vs. **gender**											
female	68%	20%	12%	26%	27%	47%	55%	32%	13%	6%	28%	66%
male	73%	16%	11%	30%	30%	40%	82%	15%	3%	6%	53%	42%
[years old]	WTW vs. **age**											
< 25	77%	19%	4%	33%	26%	41%	85%	12%	3%	11%	58%	32%
26 – 40	76%	16%	8%	25%	44%	32%	83%	17%	0%	2%	49%	49%
41 – 50	73%	22%	5%	35%	19%	46%	64%	31%	5%	2%	34%	64%
51 – 65	50%	22%	28%	22%	17%	61%	41%	38%	21%	5%	22%	73%
> 65	28%	14%	58%	6%	6%	89%	44%	36%	20%	4%	12%	84%
using this PT route [days/week]	WTW vs. **trip frequency**											
5 – 7	72%	21%	7%	31%	26%	42%	77%	18%	4%	0%	29%	71%
2 – 4	77%	15%	7%	28%	34%	38%	64%	27%	8%	6%	40%	55%
1	55%	5%	39%	13%	30%	58%	50%	29%	21%	7%	42%	51%
< 1	58%	22%	20%	22%	24%	54%	59%	28%	13%	6%	39%	55%

time range between 0 and 20 [mins].

Based on the above findings, we compute the value-of-time crowding multipliers for a sample 15-minute journey in urban PT network (Table 7). The post-COVID crowding multipliers are, likewise, higher for the cases (A) and (C), and lower for the case (B). Relative changes against the pre-COVID rates are around 5 % to 10 %. This compares similar, albeit lower, to findings in the recent literature on post-COVID changes in crowding valuations (30).

5. Conclusions

This study examines pre- vs. post-COVID willingness to wait (WTW) to reduce or avoid overcrowding in urban PT networks. To this end, we compare data from stated-preference (SP) surveys conducted in 2019 and 2022 in Krakow (Poland) and estimate the resultant discrete choice models. Our investigation provides unique insight into COVID-related changes in prospective utility of real-time crowding information (RTCI) and factors influencing WTW probability in bus and tram

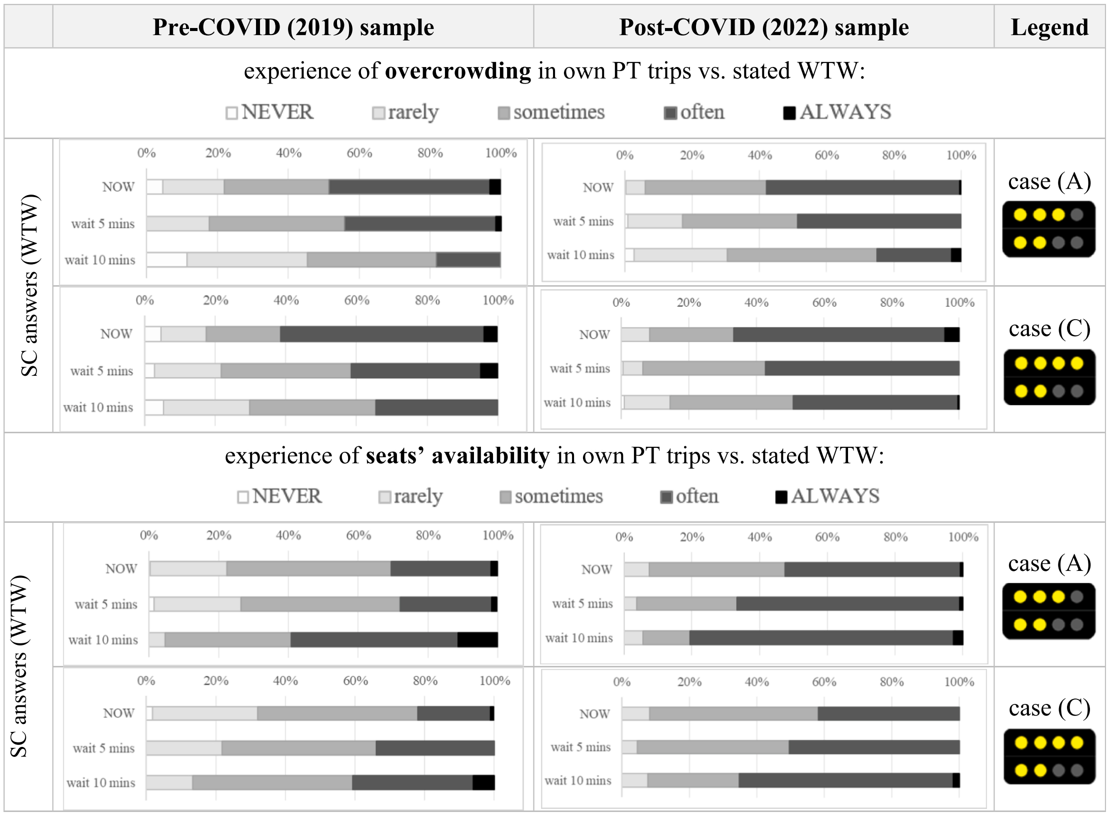

Fig. 3. Survey results – influence of own PT travel experience upon stated WTW, before (left) vs. after (right) COVID pandemic.

Table 4
Mixed logit estimation results – base model of the WTW with RTCI.

Coefficients		Pre-COVID (2019)			Post-COVID (2022)		
		estimate	*std. err.*	*p-value*	estimate	*std. err.*	*p-value*
β_{RTCI}^{3-2}		1.828	*0.226*	***	2.144	*0.173*	***
β_{RTCI}^{4-3}		5.294	*0.333*	***	3.540	*0.273*	***
β_{RTCI}^{4-2}		5.510	*0.481*	***	6.598	*0.225*	***
β_{wt}	μ	−0.705	*0.060*	***	−0.628	*0.032*	***
	σ	0.286	*0.045*	***	0.234	*0.018*	***
initial log-likelihood:		−1380.9			−1734.3		
final log-likelihood:		−816.5			−1141.6		
LL ratio test:		1128.4			1243.4		
adjusted rho-square:		0.396			0.353		
sample size:		377			424		

Significance codes (p-value): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

journeys.

Findings show that while pre-COVID WTW was primarily driven by the possibility of avoiding overcrowding in the first departure, the post-COVID WTW preferences are strongly associated with the expected crowding reduction in the second departure as well. In the post-COVID analysis, the propensity to wait has declined if overcrowded conditions (RTCI lvl 4) can be reduced to 'moderate standing' crowding only (RTCI lvl 3). A 5-minute wait is acceptable for ca. 45 % of respondents, which is significant but substantially lower than pre-COVID rate of 70 %. In contrast, however, the WTW with RTCI has substantially increased post-COVID if skipping the overcrowded conditions (RTCI lvl 4) allows to board a second departure with seats available (RTCI lvl 2). A short 5-minute wait is almost universally acceptable (ca. 90 % post-COVID vs. 75 % pre-COVID), and over 50 % of post-COVID users accept a 10-minute wait. Otherwise, WTW attitudes remain rather similar in case of shifting from 'moderate standing' crowding (RTCI level 3) to a later departure with seats available (RTCI level 2), with slightly lower acceptance of longer, 10-minute wait (from 12 % pre-COVID to 8 % post-COVID).

Table 5
Mixed logit estimation results – extended model of the WTW with RTCI.

Coefficients		Pre-COVID (2019)			Post-COVID (2022)		
		estimate	*std. err.*	*p-value*	estimate	*std. err.*	*p-value*
β_{RTCI}^{3-2}		1.394	*0.385*	***	2.310	*0.463*	***
β_{RTCI}^{4-3}		4.753	*0.465*	***	3.720	*0.498*	***
β_{RTCI}^{4-2}		4.934	*0.526*	***	6.660	*0.509*	***
$\beta_{commute}$		− 0.508	*0.296*	.	− 0.377	*0.259*	
$\beta_{age50-65}$		0.597	*0.491*	.	0.328	*0.253*	
$\beta_{age65plus}$		1.812	*0.437*	***	0.669	*0.343*	*
$\beta_{timecrit}$		− 1.625	*0.224*	***	− 0.548	*0.176*	***
β_{female}		0.354	*0.209*	*	0.533	*0.201*	***
β_{ivt}		0.043	*0.008*	***	− 0.007	*0.001*	
$\beta_{past\_overcrowding}$		− 0.340	*0.235*		− 0.104	*0.191*	
β_{past_seats}		0.047	*0.219*		0.187	*0.190*	
β_{wt}	μ	− 0.612	*0.051*	***	− 0.603	*0.031*	***
	σ	0.158	*0.025*	***	0.209	*0.017*	***
initial log-likelihood:		− 1380.7			− 1736.5		
final log-likelihood:		− 780.8			− 1119.3		
LL ratio test:		1198.8			1288.1		
adjusted rho-square:		0.406			0.365		
sample size:		377			424		

Significance codes (p-value): 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Model outputs show that post-COVID utility of RTCI is higher relative to other choice attributes, as long as information indicates no standing crowding conditions of second departure (RTCI lvl 2).

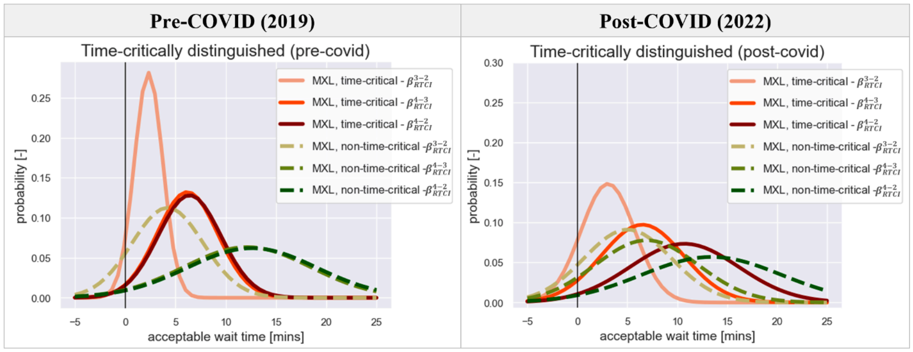

Fig. 4. Distribution of waiting time acceptance with RTCI, according to the MXL modelling results.

Table 6
Acceptable waiting times with RTCI, according to the MXL modelling results – across all the trips and distinguished by their time-criticality.

acceptable wait time [mins] - mean, *(90% CI)*	Pre-COVID (2019)			Post-COVID (2022)		
	all trips	time-crit. trips	non-time-crit. trips	**all trips**	time-crit. trips	non-time-crit. trips
case (A)	3.2 *(-2.5 to 8.9)*	2.3 *(0.1 to 4.6)*	4.2 *(-1.5 to 9.9)*	4.1 *(-1.5 to 9.7)*	3.1 *(-1.2 to 7.4)*	5.0 *(-2.1 to 12.1)*
case (B)	8.9 *(-0.6 to 18.4)*	6.2 *(1.2 to 11.1)*	12.1 *(1.8 to 22.4)*	6.7 *(-0.5 to 13.9)*	6.5 *(-0.2 to 13.2)*	6.9 *(-1.5 to 15.3)*
case (C)	9.3 *(-0.4 to 19.0)*	6.4 *(1.3 to 11.5)*	12.6 *(2.1 to 23.1)*	12.1 *(2.1 to 22.1)*	10.8 *(1.8 to 19.8)*	13.4 *(1.9 to 24.9)*

Table 7
Value-of-time crowding multipliers for a sample 15-minute PT journey, acc. to MXL modelling results.

VoT crowding multiplier - mean	**Pre-COVID (2019) - all trips**	**Post-COVID (2022) - all trips**
case (A)	1.21	1.28
case (B)	1.59	1.45
case (C)	1.62	1.81

Compared against pre-COVID results, most trip- and population-related factors seem to have relatively lower influence upon WTW with RTCI. This suggests that WTW has become a more universal phenomenon and relevant for time-critical trips as well. Demographic factors retain their relevance, as propensity to wait grows noticeably for middle- and older-age groups (from 40 years of age onwards in the post-COVID sample), and has become higher for female travellers as well. Acceptable waiting time thresholds are relatively similar, regardless of trip time-criticality. Their post-COVID average rates oscillate between 4 and 12 [mins] (compared to 3 – 9 [mins] in the pre-COVID sample), yet according to distribution plots the acceptable thresholds may reach up to 15 – 20 [mins] (or even further) in individual cases.

This study contributes to growing stream of research on the COVID-19 behavioural impacts in urban PT networks, particularly with regards to overcrowding effects. As noted in state-of-the-art, post-pandemic travel choices involve greater considerations of travel safety and comfort aspects. Our findings expose further how perceptions and attitudes towards RTCI information have changed as a consequence of COVID-19 crisis. While seat availability itself may not be a crucial decision factor in short-range, urban PT trips, passengers seem to attach relatively greater weight to the RTCI content and displayed differences in crowding levels of PT vehicles. The post-COVID value-of-crowding multipliers are higher by up to ca. 10 %, which is comparable with (albeit lower than in) recent state-of-the-art findings, e.g. (Basnak et al., 2022; Aghabayk et al., 2022; Cho and Park, 2021). Furthermore, our findings indicate that passengers' own experience of PT on-board (dis) comfort can play a potential role in WTW with RTCI. Interestingly, frequent exposure to PT overcrowding effects may induce more 'crowding-resilient' choices and decrease passengers' interest in delaying their boarding decisions at stops. On the contrary, propensity to wait with RTCI seems to grow among users that experience more often seated PT travel conditions.

Our findings underline the potential of WTW with RTCI to become an important travel behaviour phenomenon. While lack of reliable information inhibits the passengers' options of choosing a second (or later) PT departure (Kattan and Bai, 2018; Shelat et al., 2022b), the RTCI availability would directly address this uncertainty gap and increase the utility of alternative PT departures.

Analytical outputs of this study are implementable in PT simulation (assignment) models and can support planning and management of network operations. Study conclusions can also deliver valuable underpinning for practical design of future RTCI systems. Since our findings show that post-COVID responses to crowding information have become more nuanced, this may reflect growing relevance of the provisioned RTCI content in urban PT networks. For instance, the post-COVID studies conclude that travellers are likely to be wary of on-board crowding at lower occupancy levels (Shelat et al., 2022a), which is reflected in our estimates of the WTW with RTCI. Urban PT users may be nowadays more interested in the RTCI indicating not just the threshold of on-board overcrowding (as in our pre-COVID outcomes), but distinguishing lower and moderate crowding conditions as well.

Conclusions of this work underpin that RTCI systems may play an advantageous role in the post-pandemic recovery of urban PT systems. Our study complements the emerging consensus in state-of-the-art that RTCI systems can help limit the risk of contagion spread and stimulate the regrowth of PT ridership (Bansal et al., 2022; Downey et al., 2022; Tirachini and Cats, 2021). Information on the possibility to travel in lower on-board conditions can directly address the elevated concerns related to PT crowding and associated safety (and/or infection exposure) risks. This would help reassure the prospective users and could greatly enhance the perceived attractiveness of PT service quality. Moreover, timely and accurate RTCI can emerge as an effective travel demand management tool in future PT networks. By raising the awareness of available PT system capacity in real-time, such information could help travellers make more informed decisions. Consequently, it will encourage shifts towards otherwise less-popular connections, and thereby support more balanced and efficient utilisation of PT network resources, and decrease exposure to risks of PT overcrowding.

Our study is not exempt from certain limitations that can be addressed in future works. Among these, the common caveats of SP investigation apply, as these are notable for overestimation bias in crowding valuations. Revealed-preference validation of actual WTW behaviour is highly desirable, and will be only feasible with practical implementation of RTCI solutions. The stated-choice experimental setup could be extended to consider wider choice sets, including multiple departing options, longer waiting times, different RTCI configurations and representations, monetary (fare) trade-offs etc. Our investigation focuses on bus and tram journeys in urban PT context, while longer-range rail trips may involve different safety perceptions and crowding valuations, including likely higher emphasis on seat availability. Importantly, longer-term monitoring of RTCI, and crowding valuations in general, is needed to verify whether post-COVID travel preferences have already stabilised and eventually converged (or not) with the pre-COVID picture. Meanwhile, the potential of RTCI in post-pandemic recovery of PT ridership can be already exploited and utilized in PT simulation and cost-benefit models, facilitating the adoption of RTCI as effective dynamic passenger information system in the near future.

CRediT authorship contribution statement

Arkadiusz Drabicki: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Oded Cats:** Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Rafał Kucharski:** Data curation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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